

The Design and Implementation of Neural Network Encoding and Decoding

Wei XIAO^{*,1,2}, Yong AI¹ and Zhicheng DONG²

¹ *Electronic Information School, Wuhan University, Hubei 430072, China*

² *School of Engineering, Tibet University, Lhasa 850000, China*

Abstract — An artificial neural network can be applied in decoding traditional code words. However, artificial neural network encoding has rarely been explored. A forward artificial neural network encoder is proposed, which adopts a self-organizing map (SOM) neural network as its main structure. Firstly, we built a forward neural network according to the dimension of source bits and codeword bits. Secondly, we chose a proper distribution of weight sets. Thirdly, we initialize the weight sets using an appropriate algorithm. Finally, we check the uniqueness of the code word sets until a match is found. In the decoding process, a multi-layer perceptron network (MLPN) is adopted as the neural network decoder. Firstly, we construct the MLPN according to the dimension of source bits and codeword bits. Secondly, we train the MLPN with the codeword sets generated by the forward neural network. Then, we stop the training process until total error is minimum. Finally, we accept and decode code word sets. Actual simulation tests show that both neural network encoding and decoding are feasible. And the better performance is achieved in the condition of proper forward neural network structure and the degree of output node λ . Above all, the codeword sets generated by the neural network encoder cannot be decoded by traditional mathematical methods, which has good prospect for security communication.

Keywords - forward neural network; self-organizing map (SOM) neural network; multi-layer perceptron network (MLPN)

I. INTRODUCTION

Generally speaking, encoding and decoding are used to improve the reliability in the communication process. And specific algorithm is adopted as a relation of source bits to check bits. Low-density parity-check (LDPC) code, for example, is a typical linear block code. And the check matrix (or generating matrix) is a complete relationship between source bits and codeword bits.

Every check bit is produced by several specific source bits and corresponding check expression (according to check matrix). In decoding process, if the received codeword bits cannot match check expression, the error can be found and corrected.

At present, neural network generally is adopted as a novel method to decode traditional code, such as convolution codes[1], Turbo product codes[2], LDPC[3,12]. There are at least two types of neural network decoder.

- (1) Neural network is adopted as main architecture in the decoder [3-8]
- (2) Neural network is adopted as supportive role in the decoder [1,9]

MLPN is a typical neural network, which is generally adopted as a solution for neural network decoder [3]. Therefore, the decoder must be trained adequately by codeword sets in advance.

A Hopfield neural network is used to jointly equalize and decode information transmitted over a highly dispersive Rayleigh fading multipath channel in [4].

Based on an unsupervised recurrent neural network(RNN), optimizations for an existing decoding method are investigated in [10]. Based on radial basis function neural networks, an extrinsic information extraction

scheme and corresponding decoding algorithm are proposed in [11].

In [5], a linear block code decoder is proposed by neural network, which is easy to implement in real time and parallel computation for high speed implementation. However, the weights and activation functions of the neural network must be changed when dealing with non-binary Galois Field in order to detect and correct multiple error bits.

A soft decoding SOM (self-organizing map)-based robust VQ(vector quantization) approach is presented in [6], which is suitable for wireless communications. A novel convolution decoder based on neural network is proposed in [7], which has better performance than traditional turbo decoding technique. A novel general neural network decoder is presented in the form of symmetrical self-organizing map (SSOM) in [8], which can achieve both leaning and decoding in the same time regardless of any encoding rules.

Above all, the study on neural network decoding is mainly on decoding traditional code. However, the study on neural network encoding is rarely concerned by researchers.

Neural network encoding, adopted a neural network to encode original source bits, is a novel method to express the relationship between source bits and codeword bits. The study on neural network encoding is on the beginning stage. Several contributions are achieved in this paper:

- A workable solution is proposed, which can realize both neural network encoding and decoding.
- The rule of neural network encoding cannot be described by traditional mathematic method, which has certain confidential feature.
- The codeword sets generated by neural network decoder cannot be decoded by traditional mathematic way.

- The system is suitable for security communication

II. THE MAIN IDEA OF NEURAL NETWORK ENCODER

A. The Mechanism of Traditional Encoder

The main difference between traditional encoder and neural network encoder is generation mechanism of the codeword sets. Fig. 1 shows the architecture of traditional encoder and decoder. In traditional encoder, N original source bits are used to generate N+K codeword bits through generating matrix, which include K bits redundancy check bits. Therefore, the N+K codeword bits can be checked by check matrix in the decoding process.

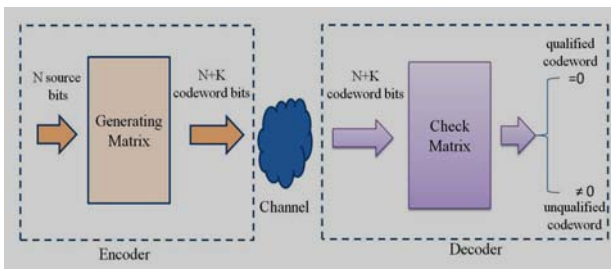


Figure 1. The Architecture of Traditional Encoder and Decoder

Naturally, generating matrix is the core of traditional encoder. Generally speaking, traditional encoder adopts several source bits to calculate corresponding check bit according to generating matrix (or check matrix). LDPC codes, for example, are constructed using a sparse bipartite graph (Fig. 2), which is another form of check matrix. Every check bit is calculated by specific bit. In Fig. 2, for instance, check bit N5 is calculated by the expression: $N_5 = B_1 \oplus B_2 \oplus B_3 \oplus B_4$.

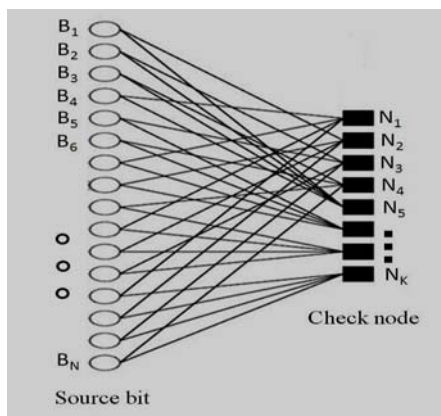


Figure 2. Sparse Bipartite Graph of LDPC Codes

In sum, there are several characteristics of traditional encoders:

- Codeword bits are generated by specific formulas or rules

- Codeword bits have relationship with original source bits
- Different rules of generating codeword bits mean different code type

B. The Mechanism of Neural Network Encoder

In neural network encoder, however, codeword sets are produced by generating neural network. Fig. 3 shows the architecture of neural network encoder and decoder. There are two main different aspects comparing to traditional encoders.

- Codeword bits are generated by generating neural network (or forward neural network), rather than generating matrix or specific formulas.
- Code type is determined by generating neural network and its own weight sets.

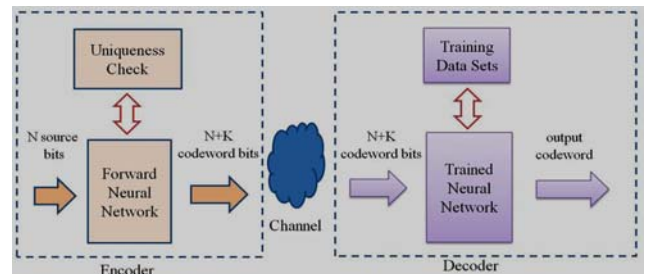


Figure 3. The Architecture of Neural Network Encoder and Decoder

In the neural network encoder, the forward neural network is adopted to transform N source bits into N+K codeword bits, which has similar function with generating matrix in traditional encoder. Forward neural network, also called generating neural network, has some difference with normal neural network, such as MLPN, SOM, etc.

Fig. 4 is a way to produce codeword sets by forward neural network. And the architecture of encoder is similar to SOM neural network. However, it is different with traditional SOM neural network as follows:

- The generating neural network only has forward process. In other words, the generating neural network has not competition and learning process.
- Forward neural network is not fully connected. In other words, any output node is connected with part input nodes via weight, rather than all connection model. It is another difference with tradition SOM neural network.
- The value weight sets' range must be in a certain range in forward neural network, which aims to guarantee result of output node within the scope permitted.
- The structure of output node is different with traditional SOM neural network(Fig. 5).

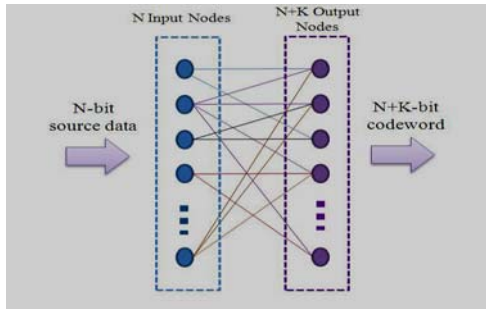


Figure 4. The Architecture of Forward Neural Network Encoder

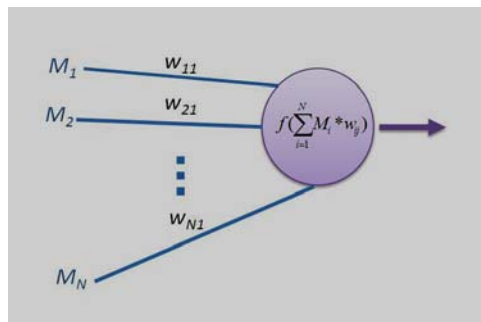


Figure 5. The Structure of Output Node

In Fig. 5, the ultimate O_j is determined by connected w_{ij} and corresponding M_i . And the actual result is determined by decision function $f()$. F_T is threshold of weight sets of decision function, which is calculated by (3).

$$O_j = f\left(\sum_{i=1}^N M_i * w_{ij}\right) = \begin{cases} 1 & O_j > F_T \\ 0 & O_j < F_T \end{cases} \quad j = 1, 2, \dots, N+K \quad (1)$$

$$w_{ij} = \begin{cases} w_{ij} & \text{input node } i \text{ and output node } j \text{ are connected} \\ 0 & \text{input node } i \text{ and output node } j \text{ are not connected} \end{cases} \quad (2)$$

$$F_T = \frac{1}{\sum_{i=1}^N \sum_{j=1}^{N+K} M_i * w_{ij}} \quad (3)$$

However, the range of weight should be in certain range according to (4):

$$w_{ij} < w_T, \quad w_T = \frac{1}{\lambda(N+K)} \sum_{i=1}^N \sum_{j=1}^{N+K} B_{ij} \quad (4)$$

$$B_{ij} = \begin{cases} 1 & w_{ij} \neq 0 \\ 0 & w_{ij} = 0 \end{cases} \quad (5)$$

And λ is the average degree of output node in forward neural network, which is average number of weight sets connected with output nodes. Generally speaking, λ is determined by (6). When λ is $N+K$, the forward neural network is fully connected by weight sets. In other words,

any output node has relationship with all input nodes. However, it is not a good option in such circumstance.

$$\lambda = \xi N / (N + R) \quad (6)$$

ξ is the degree of input node, generally within [2-6], which represents the number of related output nodes. Bigger ξ means more relationship to respond an individual input node, which results in great complexity of computing in the encoding process.

C. The Specific Steps of Neural Network Encoder

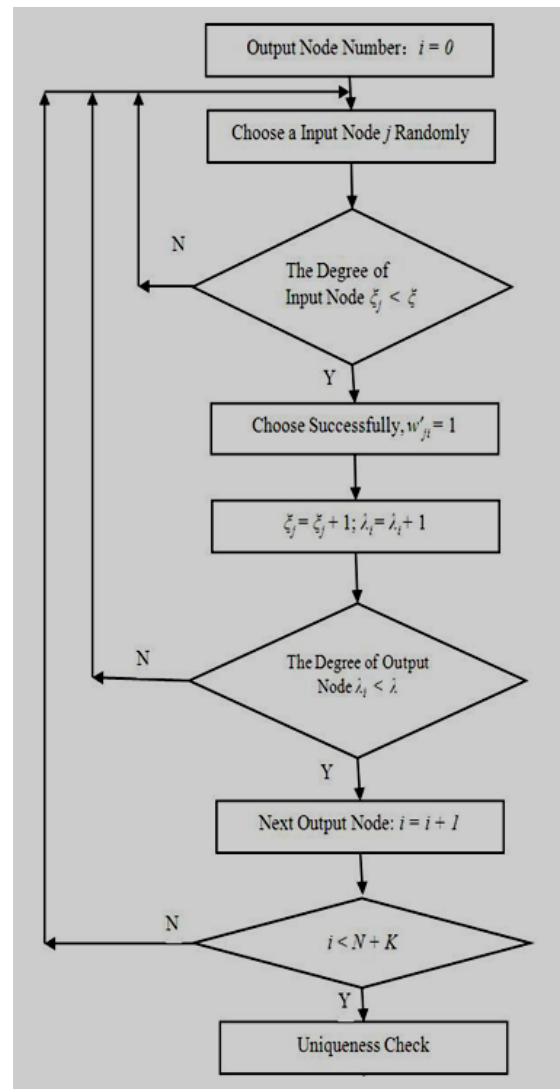


Figure 6. The Algorithm of Constructing Forward Neural Network

The neural network encoder can be implemented as follows:

- Construct a neural network according to λ , the dimension of source bits and codeword bits.
- Initialize the weight sets with a group of random number.

- Accept source bits and calculate codeword bits according to (1)-(6).
- Jump to step (3), accept next source bits.
- Check the uniqueness of the codeword sets.
- In step (1), the algorithm of constructing forward neural network can be described as follow(Fig. 6):

Note: in Fig. 6, ξ_j is the degree of input node j . λ_i is the degree of output node i . w'_{ji} is the weights tag, which is used to multiply corresponding w_{ij} in initialization stage. And default value of w'_{ji} is zero.

Fig. 7 shows the algorithm of checking uniqueness.

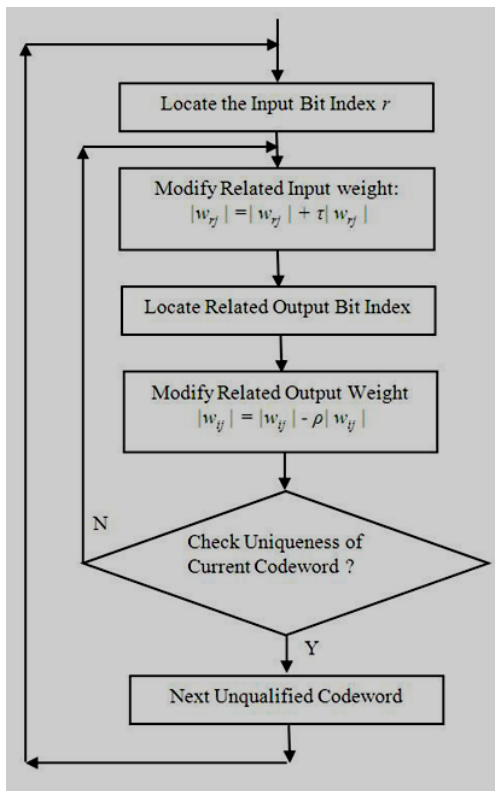


Figure 7. The Algorithm of Checking Uniqueness

Note: in Fig. 7 τ is learning rate, which is to strengthen the impact of specific input bit by increasing related weight sets, and ρ is suppressing rate, which is to reduce the impact of related output bit by decreasing related weight sets. Generally speaking, learning rate τ is much bigger than suppressing rate ρ .

III. THE DESIGN OF NEURAL NETWORK DECODER

A. The Solution of Neural Network Decoder

The codeword generated by forward neural network encoder cannot be decoded with traditional way. Firstly, the relationship between source bits and codeword bits cannot be described by a generating matrix or expression. Secondly, the rule generated codeword of forward neural network encoder cannot be expressed by traditional mathematical way. Finally, the forward neural network in the encoder is a

black box, which records the encoding rules. However, the weight sets, the structure and the algorithm of forward neural network are the whole black box.

Therefore, using a neural network as a decoder is a feasible way to decode the codeword sets generated by neural network encoder. There is a typical method to achieve the encoding function: MLPN.

The Fig. 8 below is the architecture of MLPN decoder. Thus, the decoder has two stage: training stage and decoding stage. In training stage, the MLPN is trained by a group of codeword sample sets, which are constructed by original source bits and corresponding codeword bits generated by forward neural network. In decoding stage, the trained MLPN accepts codeword bits and calculates the ultimate output result.

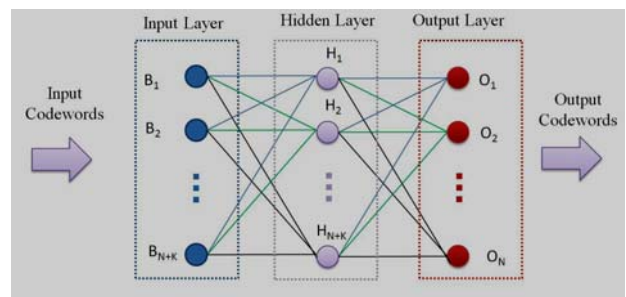


Figure 8. The Architecture of MLPN Decoder

B. The Specific Steps of Neural Network Decoder

There are two stages in neural network decoder: training stage and decoding stage. Training stage is a learning process from training sample sets, which are composed of codeword bits and source bits. The specific steps are as follows:

- Generate training codeword data sets from encoder(forward neural network)
- Construct MLPN according to the size of training sample sets.
- Train the MLPN with specific algorithm until convergence

After training stage, the MLPN can be adopted as decoder to decode codeword bits. And the MLPN is a traditional decoder in decoding stage.

- Accept codeword bits and calculate the result layer by layer
- Export the result of the decoder (output layer of MLPN)
- Jump to step (1), and accept next code word bits.

IV. CONCLUSION

A. The BER Comparison of Different λ

Form the Fig. 9 above, conclusions are reached as follows:

- BER decreases when SNR increases
- BER fluctuates when λ changes

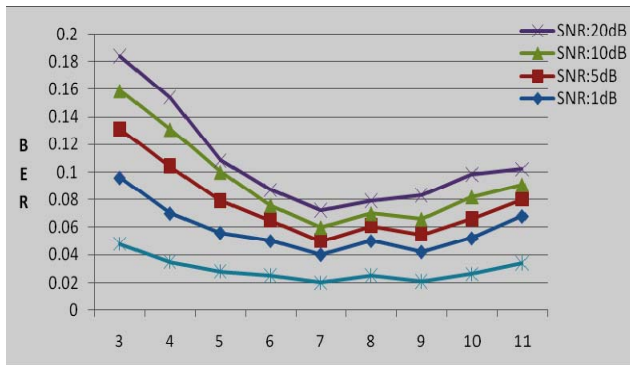


Figure 9. The BER Comparison of Different λ

Good BER can be obtained by choosing a proper λ in the same SNR. On the other hand, high λ means more complex computation. In such condition, more resource will be needed in the system. In general, proper λ is generated by (6).

However, there is a possibility of uniqueness check failure. That is to say: any N source bits has not the only corresponding $N+K$ codeword bits. There are two factors for such failure.

- The structure of neural network is not suitable for current codeword sets
- The weight sets should be modified to match the codeword sets

As to factor (2), the algorithm of uniqueness check is to solve the problem. Uniqueness is guaranteed by modification of weight sets. On the other hand, future study can focus on the modification of neural network structure to guarantee the uniqueness of encoder.

B. Prospect

Neural network encoding is a channel coding which has security feature. The whole rule of encoding is neural network itself and its weight sets. Therefore, such encoding algorithm is a block box, which cannot be described by traditional mathematic method.

Both encoding and decoding are adopted neural network. The specific rule of encoding and decoding is stored in whole neural network in distributed way. Furthermore, the parallel mode of neural network will be increase the reliability and speed greatly, which has certain prospect in future application.

ACKNOWLEDGMENT

This research is supported by Aviation Science Foundation of China (No. 201351S5002), the National Science Foundation of China (NSFC, No. 61561046), the Key Project of Science Foundation of Tibet Autonomous Region (No.2015ZR-14-3) and the 2015 Outstanding Youth Scholars of Everest Scholars Talent Development Support Program of Tibet University.

REFERENCES

- [1] C. Q. Nadalinia, A. H. Fazlollahi, R.S. Mohammad, G. Mehdi, "An Improved soft decision method in Viterbi decoder using artificial neural networks", 1st Iranian Conference on Pattern Recognition and Image Analysis, PRIA 2013.
- [2] M. E. Buckley, S. B. Wicker, "A Neural Network for Predicting Decoder Error in Turbo Decoders", IEEE COMMUNICATIONS LETTERS, vol. 3, no.5, pp:145-157, 1999.
- [3] A.R. Karami, A.M. Ahmadian, H. Tavakoli, "Multi layer perceptron neural networks decoder for LDPC codes", 5th International Conference on Wireless Communications, Networking and Mobile Computing, 2009
- [4] H.C. Myburgh, J.C. Olivier, "A low complexity Hopfield neural network turbo equalizer", Eurasip Journal on Advances in Signal Processing, vol. 2013, no. 1, 2013
- [5] A.S. Hadi, "Linear block code decoder using neural network", Proceedings of the International Joint Conference on Neural Networks, pp: 1111-1114, 2008.
- [6] C.S. Leung, H. Chan, W.H. Mow, "Soft-decoding SOM for VQ over wireless channels", Neural Processing Letters, vol 24, no 2, pp: 179-192, 2006
- [7] S.M. Berber, V. Keeman, "Convolutional decoders based on artificial neural networks", IEEE International Joint Conference on Neural Networks - Proceedings vol. 2, pp:1551-1556, 2004.
- [8] W. Xiao, Y. Ai, "The Design and Implementation of General Symmetrical Self-Organizing Map Decoder", The Open Cybernetics & Systemics Journal, vol .9, pp:1307-1310, 2015.
- [9] J. Yuan, C. He, W. Gao, J. Lin, Y. Pang, "A novel hard decision decoding scheme based on genetic algorithm and neural network", Optik, vol. 125, no. 14, pp: 3457-3461, 2014
- [10] H. Klaus; G. Jürgen; C. Edmund, "Improving the performance of a recurrent neural network convolutional decoder", IEEE International Symposium on Signal Processing and Information Technology, pp: 889-893, 2007
- [11] X. Liu, J. Cai, "Gaussian function assisted neural networks decoding algorithm for turbo product codes", Lecture Notes in Computer Science, vol. 7952, no. PART 2, pp: 586-596, 2013.
- [12] R. Annauth, C.S. R. Harry, "Neural network decoding of turbo codes", Proceedings of the International Joint Conference on Neural Networks, vol. 5, pp: 3336-3341, 1999.